Classifying Skin Lesion Images Using Adaptive Boosting

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Background

Melanoma:
- The most serious form of skin cancer
- Responsible for more than 125,000 deaths in the United States from 1999 to 2013[1]
- Early detection can dramatically increase the survival rate of melanoma:
  - » 50 percent in late stages when lesion is ≥ 4 mm in depth
  - » 95 percent if caught when the lesion is < 1 mm in depth[2]

Diagnosis:
- Physicians use the ABCDEs (asymmetry, border irregularity, color variegation, diameter ≥ 6 mm, and evolution of size/shape/color) to classify a skin lesion as either benign or malignant.
- If the lesion is considered suspicious, the physician will perform a biopsy for a pathologist to analyze it.

Current Limitations:
- Biopsy is costly in terms of time and money.
- Dermatologists do not always classify skin lesions accurately.
- Convolutional neural networks (CNNs) have good accuracy but are computationally intensive[3].

Feature Extraction

Data Set:
- Classification models were trained on a set of 700 photographs of skin lesions (535 benign and 135 malignant) from the International Skin Imaging Collaboration (ISIC).
- The testing set has 200 images from the same source.

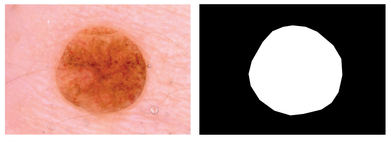


Figure 1: A benign lesion and its binary segmentation mask, where the lesion area is white and skin/background is black.

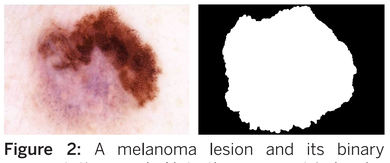


Figure 2: A melanoma lesion and its binary segmentation mask. Note the asymmetric border and varied colors within the lesion as compared to the benign lesion.

Texture Features:
- Extracted from the grayscale images using R's `radiomics` package
- First-order features: Features only depending on the pixels themselves
- Second-order features: features depending on the relationship between two or more pixels
  Ex: The gray level co-occurrence matrix shows how many neighboring pixels have the same gray level and in general measures the smoothness of the image.

Color Features[4]:
- Extracted from the RGB (red, green, blue) images
- Mean and standard deviation of each color channel
- Mean and standard deviation of the intensity channel (**Equation 2**)
- Color variegation (**Equation 3**) for each color channel and for the intensity

$$I(x,y) = \sqrt{R^2(x,y) + G^2(x,y) + B^2(x,y)}$$

Equation 1: Definition of the intensity channel for each pixel I(x, y) in the image.

$$cv_R = log\frac{\sigma(R)}{\mu(R)}$$

Equation 2(a): Parameter for the color variegation of the red channel. (Calculation for green and blue channels is analogous.)

$$cv_I = log\frac{\sigma(I)}{\mu(I)}$$

Equation 2(b): Parameter for the color variegation of the intensity channel.

Asymmetry and Circularity[5]:
- According to the ABCDE principles, lesions that are more asymmetric (**Equation 3**) should be more likely to be malignant.
- Lesions that are more circular (**Equation 4**) should be less likely to be malignant.

$$SD = \frac{1}{n}\sum_{i=0}^{n-1}\|Pi - \widehat{Pi}\|^2$$

Equation 3: Measure of asymmetry. The symmetry distance (SD) is the displacement of each vertex when the skin lesion is transformed into a symmetric shape.

$$circ = \frac{4\pi A}{P^2}$$

Equation 4: Measure of circularity as a function of area *A* and perimeter *P*. Objects with ratio closer to 1 are more circular, while objects with ratio closer to 0 are less circular.

Model Creation and Selection

Diagnostic Measures:

$$TPR = \frac{TP}{P} \; or \; \frac{TP}{TP+FN}$$

Equation 5(a): Sensitivity: The true positive rate (TPR), or percentage of malignant lesions that are correctly identified as malignant.

$$TNR = \frac{TN}{N} \; or \; \frac{TN}{TN+FP}$$

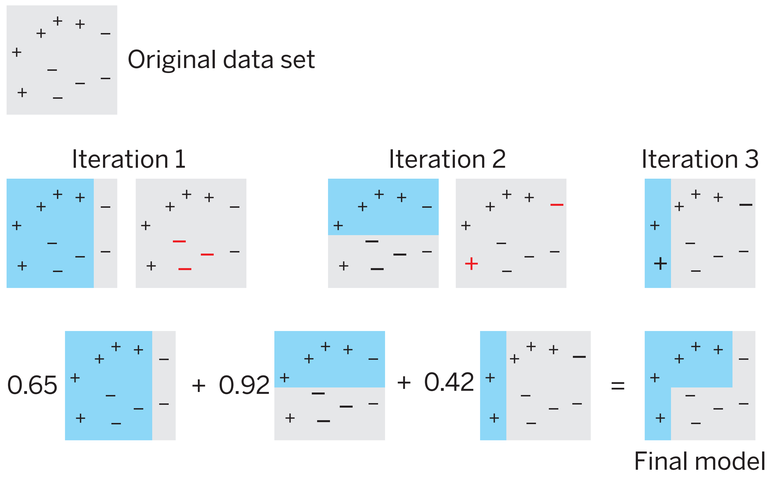
Equation 5(b): Specificity: The true negative rate (TNR), or percentage of benign lesions that are correctly identified as *not* being malignant.

$$avg\ acc = \frac{TPR+TNR}{2}$$

Equation 5(c): Average accuracy: Measures how well the classifier correctly identifies benign and malignant cases.

AdaBoost: "Adaptive Boosting"
- Fit using `ada` package in R
- Uses many weak learners (bad at classification) to create a strong learner (good at classification)
- Iterative process
- When an image is misclassified, it is given more weight in the next iteration[6].

Tuning:
- Choose optimal parameters:
  - » Exponential loss function
  - » Number of iterations = 50
- Select best feature set:
  - » First-order features
  - » Color features
  - » Circularity
  - » Including more features makes model performance worse.



		Truth	
		Benign	*Malignant*
Predictions	*Benign*	112	10
	Malignant	50	28

Figure 3: Confusion matrix for testing set using AdaBoost model. Correct predictions are along the diagonal.

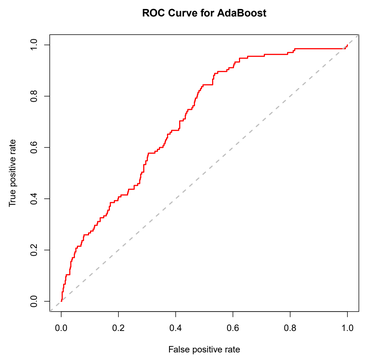


Figure 4: Receiver operating characteristic (ROC) curve for AdaBoost model based on 10-fold cross validation repeated 10 times. Ideally, the curve should appear hyperbolic (indicates high sensitivity and specificity).

Conclusion

We fit several models to classify skin lesions as benign or malignant:
- Support vector machine (SVM)
- Random forest
- Neural network
- AdaBoost

The AdaBoost model performed best.
Sensitivity: 0.736
Specificity: 0.691
Average accuracy: 0.714

Dermatologists achieved about 65.8 percent accuracy[3].

References

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